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Reflection on the Construction and Impact of an Adaptive Learning Ecosystem

Réflexion sur la conception et l'impact d'un écosystème d'apprentissage adaptatif

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Abstract

Emerging technologies are enabling adaptive learning systems to develop. This specific system consists of several models, including a learner model, domain knowledge model, instructional model, learning analytics model, and adaptive engine model. This paper reviewed multiple studies and highlighted the importance of refining each model in the context of creating a conceptual framework. We also proposed a metacognitive auxiliary model and an adaptive assessment model. The objective is to advance research into logical transitions in the internal structure of an adaptive learning ecosystem through the interpretation of different approaches, technologies, and solutions that facilitate the decision-making processes.

Keywords

Ecosystem, adaptive learning, didactics, evaluation.

Résumé

Les technologies émergentes permettent l'évolution des systèmes d'apprentissage adaptatifs. Ce système spécifique se compose de plusieurs modèles, notamment un modèle d'apprenant, un modèle de connaissance du domaine, un modèle d'enseignement, un modèle d'analyse d'apprentissage et un modèle de moteur adaptatif. Cet article recense plusieurs études et souligne l'importance d'affiner chaque modèle dans l'optique de la création d'un cadre conceptuel. Nous proposons également un modèle auxiliaire métacognitif et un modèle d'évaluation adaptatif. L'objectif est de faire progresser la recherche de transitions logiques dans la structure interne d'un écosystème d'apprentissage adaptatif grâce à l'interprétation de ces approches, de ces technologies et de ces solutions qui facilitent les processus décisionnels.

Mots-clés

Écosystème, apprentissage adaptatif, didactique, évaluation.

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Introduction

Although the COVID-19 pandemic has caused unprecedented disruption of the learning environment (Bozkurt et al., 2022; Pokhrel & Chhetri, 2021; Van der Graaf et al., 2021), it has simultaneously accelerated a number of innovative initiatives based on various aspects of Industry 4.0 technologies. Education 4.0, which aims to transform contemporary education by opening innovative models and dynamics of action around new standards, mobilizes a broad coalition of relevant stakeholders to drive systemic change (Rahim, 2021). In parallel, the Education 5.0 paradigm, in the context of Industry and Society 5.0, emphasizes effective, personalized, adaptive, and quality-oriented learning (Aprilisa, 2020; Darmaji et al., 2019). This may mean a gradual shift towards values-based and human-centred digital social innovations in teaching and learning (Carayannis & Morawska-Jancelewicz, 2022). Thus, in the post-COVID-19 pandemic era, higher education must rethink how to combine and integrate the benefits of blended training to enable the development of adaptive learning ecosystems.

Adaptive learning refers to the methodologies, techniques, and tools to improve the learning mechanism through learning analytics, optimizing learning, adjusting content types or levels, customizing learning-sequence activities, and providing adaptive feedback and remedial solutions according to specific needs (Capuano & Caballé, 2020; Kabudi et al., 2021). The transformation of adaptive instruction models to adaptive learning models is critical in enhancing the adaptive capabilities of both the systems and the learners. This involves redefining adaptive learning and the roles and behavioral approaches of stakeholders. It enhances performance and quality at the level of hybrid training in higher education addressed to the industry of the future. The present research shows that the interpretation, construction, and impact of adaptive learning remain questionable due to varying contexts. There are two groups of characteristics that are central to adaptive learning: First, diversity and adaptivity, since training instructions, learning content, learning paths, and learning strategies adapted for specific learners may or may not be appropriate for others, given that in many situations many users learn via tutoring systems or pedagogical agents where teachers take on various roles such as mentor or consultant when on-demand assistance and intervention are required. Second, adaptability and personalization, since the learning objectives, learning-sequence activities, and cognitive strategies recommended for groups of similar learners may or may not be appropriate for some of them, given that in many situations the decision-making abilities of many users may not be up to prioritizing personal learning objectives among these various recommendations, where systems such as adaptive educational hypermedia are designed to be flexible and user-compatible (Sakkinah et al., 2022).

This synthesis of the literature reviews the theoretical concepts and examines a possible future of adaptive learning, especially when emerging educational artificial intelligence is applied to enhancing learners' adaptive capabilities in future learning ecosystems. The theoretical models of adaptive learning and its relevant terms are defined. Different approaches to adaptive learning design are classified for reflecting on the sustainable implications of developing hybrid, flexible and logically feasible implementation mechanisms. The generic reference models, modelling techniques, and analytics for implementing classical adaptive learning systems are also studied. These models and techniques are designed to improve the design of adaptive teaching and to optimize learning path recommendations. Meanwhile, this study incorporates two models into the standard framework for implementing a commonly defined adaptive learning ecosystem, which may enhance personalized and adaptive learning.

Through this synthesis, our goal is to identify criteria for measuring the impact of adaptive learning systems. To that end, we look at different indicators, including performance, logic, feasibility, and sustainability. We provide a common reference for evaluating all of these initiatives according to objectively comparable criteria, despite their potentially different natures. Finally, we make recommendations for solving the problems identified, which may prove useful for future work on the effectiveness of adaptive learning.

Background and Motivation

To begin a meaningful illustration of adaptive learning theory and practice, we need to conceptualize an ideal framework based on the contextual background to help us rethink what innovative, feasible, and sustainable solutions are and to guide our understanding of them. This framework focuses on investigating adaptive learning as a multi-dimensional, multi-level exploration of the phenomena, problems, methods, techniques, and patterns of contemporary learning. The insights provided by different parties can be particularly helpful and influential, especially when the implementation of adaptive learning is not only the responsibility of teachers. This is because adaptive learning benefits tremendously from having a multi-disciplinary approach: the different perspectives lead to improved performance, logical feasibility, and sustainability. When considered from a pedagogical engineering perspective, developing the systems for adaptive learning implementation is therefore a joint action by pedagogical engineers, system designers, etc., (Zargane et al., 2023). From the epistemological perspective, it is knowledge innovation engineering, which is the open innovation of domain knowledge experts, including teachers and learners, in developing adaptive learning processes to facilitate knowledge transfer and value sharing for a sustainable society (Berding et al., 2021). And from the didactic perspective, it is how didactic engineers and researchers work with teachers to design logical and feasible instruction, teaching and learning processes, analysis, and assessment programs based on a knowledge of learning theories and methods that are dynamically adapted to learning needs and goals (Grugeon-Allys et al., 2022). The learning perspective illustrates the process by which learners construct learning trajectories, and develop cognitive strategies and metacognitive abilities in technology-reinforced, self-regulated, adaptive, collaborative, and socially regulated learning environments (Lhafra & Abdoun, 2023; Park et al., 2023; Sobocinski et al., 2022). The feedback and records generated can be helpful for teachers and learning analysts to guide the design of adaptive interventions. In general, we are looking for an anchor based on all these insights to identify a reassuring mental anchor (map) that can serve as a benchmark to help us reorient ourselves with a more innovative and sustainable adaptive learning ecosystem.

Adaptive learning systems can be interpreted differently due to the heterogeneity of projects and the visions of experts across disciplines. Although intelligent tutoring systems, adaptive learning systems, and recommender systems have been identified as having and varying degrees of capability (Kabudi et al., 2021), they are all categorized as adaptive intelligent learning or tutoring system due to the similarity of adaptation indicators and elements (Martin et al., 2020). Moreover, the versatility and agility of a system are not necessarily the only criteria for evaluating whether it is adaptable and adaptive. Adaptive learning transformation requires multiple reviews based on different approaches. The interdisciplinary approach is designed to allow a more holistic interpretation of the phenomenon of adaptive learning engineering transformation. The transdisciplinary approaches allow the combining of theoretical models, logical approaches, and practical considerations in the development of adaptive learning mechanisms. These efforts enable the creation of a framework dedicated to improving the construction of an adaptive learning ecosystem, as well as reflections on the sustainable implications.

Method

Critical interpretive synthesis (CIS) was developed for multi-disciplinary and multi-method evidence, which involves an iterative approach to refining the question and searching and selecting content (Edwards & Kaimal, 2016). In this review, we used CIS to explain, argue, and evaluate multiple studies on the theoretical models of adaptive learning design, systems, and technologies. This methodology allowed for exploration of the relevant concepts, and enrichment of the perspectives by critically combining the different literature and iteratively analyzing them using thematic synthesis.

A total of 52 scientific publications that met the eligibility criteria were assessed.

- The key phrases, such as adaptive learning, personalized learning system, adaptive learning ecosystem, open learner model, didactic of adaptive learning, and evaluation, are included in the article titles.
- The objectives, adaptive indicators, modelling methods, techniques, and types of systems are well-defined and explained.
- The system is designed for promoting self-regulated learning, adaptive co-regulated learning, and socially shared learning purposes.

Theoretical Framework

Adaptive Learning

The theoretical underpinnings of adaptive learning are complex and multifaceted. The interpretation of adaptive learning can be very heterogeneous when it is concerned with learning from theories of psychology and cognition. The term “adaptive” refers to the capability of learners to constantly adapt to distinct situations, to produce physically and mentally distinctive behaviours. Adaptive learning is a synchronous and asynchronous process of knowledge transformation in which learners facilitate problem-solving and knowledge construction. With the rising popularity of STEAM education, contemporary adaptive learning theory encourages learners to discover learning from examples and to acquire knowledge and skills in a problem-solving manner through practical work. Adaptive learning approaches based on Gestalt psychology and multiple intelligence learning theories emphasize the performance of learners’ psychological and situated cognitive behaviors in generating insight learning, productive thinking, and transferring learning (Alam & Mohanty, 2022; Anisimova et al., 2020). Meanwhile, adaptive learning approaches based on learning theories such as connectivism, zone of proximal development, cognitive load, and cognitive flexibility emphasize how learners develop autonomous learning with self-regulation, adaptive interaction, and self-efficacy. From the principles of educational technology, adaptive learning, which is based on the information processing theory, emphasizes the interaction between the consciousness of cognition and the ontology of learning for knowledge transmission. It integrates the characteristics of adaptivity and adaptability to provide pedagogical scaffolding, feedback techniques and tools. Simultaneously, adaptive learning incorporates static and dynamic learning analytics techniques such as descriptive analytics, predictive analytics, diagnostic analytics, inferential analytics, prescriptive analytics, cognitive and metacognitive analytics to facilitate the development of intelligence in the knowledge level and the metacognitive abilities of heterogeneous learners. The learners’ and systems’ adaptive learning capabilities are fundamental in the construction of a sustainable learning experience ecosystem. As in many situations, different types of users have distinct objectives and changing requirements in terms of improving the performance and quality of domain or specific knowledge.

Learning Ecosystem

The effectiveness of self-regulated, co-regulated, socially shared strategies for regulating the development of metacognitive systems for adaptive learning has facilitated developments in learning technologies and pedagogical applications from different levels and perspectives. This includes individual adaptive learning, adaptive collaborative learning, and adaptive symbiotic learning ecosystem.

The recent reviews suggest that there are benefits to integrating technological advancement with adaptive learning in a hybrid environment based on human-centric perspectives. Digital Twin (DT) is a promising technique comprising a multidisciplinary, multi-probabilistic simulation, a multi-dimensional digital mapping system for adaptive learning in the context of Society 5.0. The latter term refers to a super-smart social welfare system that is dedicated to addressing human needs (Carayannis & Morawska-Jancelewicz, 2022; Polat & Erkollar, 2021). The advantages of DT are that it relies on living models: it can replicate or simulate all the elements, processes, dynamics, and firmware of physical systems and entities as digital counterparts (Alam, 2023; Fuller et al., 2020; Mihai et al., 2022). It could be used to monitor, intelligently perceive, diagnose, predict, analyze, and optimize digital learner models and propose remediation strategies and solutions. The emerging technology of Cyber-Physical-Social-System (CPSS) aims to functionally integrate human beings at the social, cognitive, and physical levels into a Cognitive-Cyber-Physical System (CCPS) (Saadati & Barenji, 2023; Yilma et al., 2021). The incorporation of new technologies such as human digital twins (HDT) and cognitive digital twins (CDT) may enhance adaptive learning (Sun et al., 2021; Zhang et al., 2020).

AI learning platforms and embodied applications such as smart campuses, intelligent tutoring systems, virtual and immersive classrooms, and social robots are becoming increasingly prevalent in digital transformation. The cost-effective, flexible and reliable cloud-computing infrastructure enables the creation of an e-learning ecosystem. With the advent of technologies, it becomes realistic to implement learning management systems and social collaborative mechanisms at universities. This new ecosystem allows the collection of high-dimensional data, increases the sampling of dataset variables with measurable criteria, enables the expansion of adaptive indicators, as well as of the scope of adaptive targets, approaches, and technologies. These initiatives are expected to improve the compatibility and usability of adaptive learning ecosystems. This may help to improve performance, achieve a sustainable socio-economic impact, and bring a perception of added value and attractiveness to the adaptive learning ecosystem (i.e. higher education institution).

Adaptive Learning Design Approaches

The historical review demonstrated that the design of the classic didactic triangle model integrated various indicators with attempts to implement adaptive instruction. Thus, this synthesis of the literature elaborated on the dimensions of the didactic polyhedron of adaptive teaching and learning based on the adaptation from macro, micro, personal and social perspectives.

Macro-Adaptive Approach for Adaptation of Knowledge Goals

The macro-adaptive approach defines general guidelines for adaptive teaching, and a curriculum based on content and knowledge type. This approach is based on an initial stage with a priori and a posteriori analysis of static data and explicit knowledge by teachers with experience working with knowledge domain experts and system engineers to design adaptive instruction, tutoring, feedback, and assessment systems based on pre-set dynamic learning pathways. Deepening the innovation of macro-adapted approaches requires the construction of adaptive knowledge representation methods in conjunction with cognitive semiotics, information processing theory, and cognitive load theory, corresponding to different phases of the learning task (Brandt, 2020). Different theoretical bases of knowledge, such as factual, procedural, and metacognitive, include knowledge, cognitive, and automatic schemas. Learners train their working memory through continuous editing of cognitive rules to enhance their long-term memory storage. Teaching and curriculum design experts combine theoretical and empirical evidence to identify effective methods of knowledge mastery and transformation. Learning systems, such as adaptive instruction, (intelligent) tutoring, adaptive educational hypermedia and recommendation systems, adopt macro-level approaches being developed with more advanced capabilities for learners (Lamya et al., 2022; Sakkinah et al., 2022).

Micro-Adaptive Approach for the Adaptation of Assessment

The micro-adaptive approach involves on-task measurement with criteria and indicators that position teachers to assess how they track learners' behavior by providing scaffolding, including automatic prompts, corrections, and feedback. The behaviorist and zone of proximal development theories provide a basis for the micro-adaptive approach. The principle of instructional design is that learning in small steps based on the proximal development zone, combined with the stimulate response theory, reinforces learning through a process of trial and error. With this micro-adaptive approach, underpinned by practical work, learners engage in a gamified and immersive virtual laboratory to reinforce the learning experience. The modality for learning could be procedural learning with detailed units and knowledge points, combined with a personalized interactive scaffolding, adaptive heuristic scaffolds and emotional assistants (Lim et al., 2023).

Teaching and learning are delivered by teachers, pedagogy innovation researchers, system designers, cognitive psychologists, and data scientists who design pedagogical agents, develop analytic parameters, and capture a range of behavioural data generated by the learner's interaction with the system. Clustering these datasets to identify distinct learners' profiles has the potential to provide the evidence needed by the intelligent tutoring system or human teacher for redesigning adaptive scaffolding; and for adjusting the instructional styles and learning content based on difficulty levels and learning assessments. This type of adaptation strategy, with the implicit knowledge based on real-time tracking, combines learning analytics and data mining techniques to provide semi-automatic and intelligent automatic learning recommendations and feedback.

Personal-Trait Adaptive Approach for Individual Development

Macro- and micro-adaptive approaches may focus on the effectiveness of adaptive instruction and learning, whereas the learning experience should be enhanced through personalization and meaningful learning. Designing adaptive approaches based on personal traits requires extensive datasets, adaptive learning analytics, intelligent adaptation, and metacognitive navigation techniques. The sequence of individualized or customized learning activities is adapted to the learner through continuous differentiated analysis, formative assessment and summative assessment in real time. Indicators of adaptation include individual learners' knowledge goals, cognitive state, affective needs, learning preferences, etc., (Raj & Renumol, 2022). The theoretical underpinnings of the approaches are the Gestalt psychology of insightful learning, learning transfer, productive thinking, cognitive-psychological developmental theory of multiple intelligences, social comparison theory, (cultural-historical) constructivism, connectionism and connectivism (Corbett & Spinello, 2020; Siemens, 2005). The pedagogical principles are based on Maslow's hierarchy of needs, and motivation theory. Learners may develop professional knowledge, soft skills and adaptive capabilities through formal and informal learning, training and workshops. Adaptive learning continuously adapts and optimizes learning resources, scenarios, and intelligent textbooks, content, and pathways to suit different learning preferences. Learning preferences may be determined in the initial stages by tests or questionnaires filled out by learners when logging into the system, or it could be dynamically updated through continuous data analytics.

Adaptive metacognitive assistance, cognitive maps and intervention models such as adaptive navigators, mind mapping, and personalized learning analytics dashboards are provided to allow self-regulated learning (Carlon & Cross, 2022; Lim et al., 2023). The validation, development and innovation of adaptive learning with personal traits requires theoretical and empirical assessments based on the evidence and recordings of an individual lifelong learning cycle. Universities and educational institutions that only conduct short-term training might have difficulty accepting the feasibility of this approach.

Reflecting the Adaptive Approach From a Social Perspective

The design of adaptive approaches in the context of constructing learning environments for the integration of professional expertise requires deeper investigation of learners' aptitudes and teaching needs. The availability of massive open online classes and sources (MOOCs) and small private online classes and sources (SPOCs) allows the possibility of flipped classrooms, ubiquitous learning resources, knowledge dissemination, and maker-space, and allows the learning modalities of learners acquiring 21st-century skills to become asynchronous and flexible (Corbett & Spinello, 2020). The initial and continuous re-skilling and up-skilling programs are created with hybrid flexible measures to train learners to be more competitive and enable them to adapt in a professional work environment. The differences in learners' skill levels may be vast in a blended class, and the reflection of the construction and impacts of adaptive learning ecosystem is critical. Adaptive learning activities and simulation models should be built to allow competency-based, problem-based, project-based, and innovation-based learning in an open, intelligent and adaptive learning community. It is also an important step in fostering human intelligence-driven digital learning transformation. Cultivating interwoven intelligence is crucial in contemporary STEAM education. Hard and soft skills, and especially meta-thinking and meta-emotional intelligence, are gaining the attention of learners who might be involved in social innovation projects in the real world. Higher education institutions are expected to construct adaptive learning for personal and social needs. Learning log data are replicated not only to adapt to the individual but also the socio-economic outlook.

Implementation of an Adaptive Learning Ecosystem

The principal models of the adaptive learning system are: the learner model, the domain knowledge model, the instructional model, and the adaptive engine. This study focuses on the improvement, mainly through integration of adaptive learning analytics and assessment models, of the metacognitive auxiliary models and the feedback mechanisms to enhance both personalization and adaptivity. All of this is done through the development of each model in the adaptive learning ecosystem. Model analysis is done by studying: 1. adaptation indicators and criteria; 2. modelling methods and techniques; 3. challenges and opportunities for modelling.

Domain Knowledge Model

Domain knowledge is a knowledge engineering concept and can be defined in different ways based on the learning situation and modelling requirements. Domain experts may design concept maps, knowledge trees and skill hierarchies with different dimensions, difficulty levels and knowledge association points, possibly combined with adaptive testing and learning models, to create adaptive learning paths that meet the needs of heterogeneous groups of learners. The advances in modelling assisting and generation tools, including domain model acquisition tools, do not ensure perfect models, given that the creation and maintenance of domain models is a well-recognized bottleneck and remains a challenge in the use of automated planning. To innovate in the area of knowledge engineering systems, it is essential to develop the knowledge engineering planning model as an iterative process in the generation of effective plans, fed with an accurate model of an application in the planning engine (Lindsay & Petrick.,2022).

Learner Model

Learner modelling involves data elicitation, model representation, and maintenance, and it allows the system to provide the adaptation using the learning variables stored in the model. These variables can be classified into: conative, cognitive, metacognitive and affective categories. Well-defined and accurate adaptive criteria are critical for determining the effectiveness and sustainability of a learner model. Modelling approaches such as overlay, stereotype, Bayesian network, etc., employed algorithms and intelligent techniques, all mainly focused on the instructional contexts. The open learner model (OLM) encourages learners to actively participate in thinking about and crafting their learning. It was designed as a suitable interface model which allows the visualization and transparency of knowledge and progress for the users including learners, peers, teachers, administrators, etc., (Brusilovsky et al., 2022). It provides methods, techniques, and tools for promoting planning, navigation and other metacognitive activities that are important in the development of personalized adaptive mechanisms and for favoring deep learning (Bull, 2020; Guerra Hollstein, 2018; Hooshyar et al., 2020). Meanwhile the open social learner model (OSLM) integrates social comparison features that might improve learning motivation, achievement, and monitoring abilities, including self-reflection and self-assessment (Bull, 2020; Somyürek et al., 2020). OSLMs that use gamification and embodied cognition may be emerging as a research direction in the improvement of the adaptive learning experience.

Instructional Model

Adaptive educational systems (AES) include adaptive instructional systems (AIS), intelligent tutoring systems (ITS), and adaptive hypermedia systems (AHS). Although several studies reveal that they are focused on the strategies of teaching, tutoring, learning adaptation and recommendation, they do not necessarily lead to better personalized adaptive learning. This is due to the accent being put on technological tools to the detriment of the pedagogical aspect (Apoki et al., 2022). The components in this model were found to have diverse functions, defining the rules to access the domain knowledge model in relation to learner models, and updating the learning design, methods, and activities based on the indicators and criteria. Challenging issues, at present, still include the handling of partnership among interdisciplinary teams. In the pedagogy innovation management model, it is important to redefine and reflect on the roles and impacts of pedagogues. What innovative didactic strategies, teaching competency, learning methods, techniques, and tools can suit the construction of personalized learning systems (Brühwiler & Vogt, 2020). Which logical feasibility, viability, and sustainability issues should be taken into account for reflection on learning impacts? How could adaptive deep learning activities be designed to prompt self-regulated, co-regulated learning and self-directed learning to allow the learners to cultivate the interwoven intelligence needed to become a domain expert. Is it feasible to integrate the competency or intelligence-based learning module into the instructional model for the training of vocational professionals and social career innovators?

Adaptive (Learning Recommendation) Engine

This adaptive engine is supported by machine learning algorithms. It allows the automatic generation of a presentation model and plays a fundamental role in implementing intelligent and adaptive approaches, techniques, or recommendation rules. The adaptive engine uses multiple criteria to make its recommendations, including adaptive sources based on learner models, adaptive targets, and elements based on content or instructional models. Then it adapts the content, assessment, and sequences for the learner (El Guabassi et al., 2018; Mayrhuber & Krauss, 2022; Shawky & Badawi, 2018). The adaptive engine faces two main challenges: designing and implementing effective techniques; and using adaptive learning for a broader spectrum of combined disciplines. Future research directions for adaptive engines will require more competencies and transdisciplinary adaptive learning, involving the integration of multidisciplinary resources and interdisciplinary systems (Clemente et al., 2022).

Adaptive Learning Analytics and Assessment Models

Learning analytics play an important role in a wide range of actions. Firstly, they help with both describing learning performance and diagnosing knowledge mastery and cognitive abilities. Particularly important in predicting potential risks and prescribing both instructional decisions and recommendation resources, they ultimately help when trying to infer learning solutions. Adaptive learning analytics, as a subset of learning analytics, can analyze the above-mentioned variables about learning in addition to improving the overall implementation of personalized and adaptive learning (Sarıyalçınkaya et al., 2021). In parallel, it attempts to incorporate personal cognitive and sentiment analytics into the multidimensional metrics of learning analytics. All this is in order to create a more accurate support for adaptive learning at an individual level. Personalized adaptive learning analytics dashboards are often used as a feedback tool to support the reflective phase of self-directed learning. Due to the lack of evidence to support the measurement of learners' metacognitive processes in open learning tasks, previous efforts on adaptive learning analytics for metacognitive enhancement appear insufficient. Nevertheless, strengthening the communication of technical and theoretical foundations among domain experts is a key action **for** addressing the main challenges.

Intervention Models: Metacognitive Auxiliary Models and Feedback Mechanisms

Adaptive learning analytics develop the basis for the implementation of different types of interactive intervention models. Self-regulated learning activities include metacognitive strategies such as planning, self-monitoring, self-reflection, self-adjustment, self-assessment, and self-efficacy (Kabir et al., 2022). An adaptive intervention engine promotes co-regulation by facilitating learning-based accompaniment, which favors deep learning by providing metacognitive auxiliary and feedback. The development of adaptive support methods is more conducive to improving learners' meta-intelligence and reflective ability. Moreover, meta-intelligence, including meta-consciousness and meta-emotional intelligence, is a key skill for cultivating learners' effective self-regulation and co-regulation learning, so that they can adapt to the knowledge innovation society. Due to the heterogeneity of learners, the feedback mechanism and its types may be based on individual needs for self-discipline, learning task orientation, or process orientation to generate the recommendations. Adaptive metacognitive scaffolding is based on knowledge development goals as well as the learners' cognitive and affective needs. Self-directed learners may benefit from different types of feedback, and adaptive learning systems should have the ability to automatically provide effective feedback. Meanwhile, the construction of metacognitive support and feedback adaptation combined with psychometrics and neuroscience might be attractive and effective in the development of future and modern learning techniques (Carlon & Cross, 2022; Ramírez-Mera & Tur, 2023).

Conclusion

The common reference focuses primarily on illustrating a dynamic framework that combines extraordinary measures and assessment guidelines for the development of adaptive learning. It was created through the synthesis of theoretical models, design approaches and implementation conditions, the reflections of relevant indicators, and criteria for the construction of a logical, feasible and sustainable adaptive learning ecosystem. It is oriented toward the perspective of symbiotic education, fusing the bodies of knowledge of ontology, epistemology, experience, and cognition (Kinsner, 2021; Nguyen et al., 2022).

In this synthesis, we began by interpreting the logical approach of learning theories to guide educators in designing adaptive learning activities to meet the needs of a heterogeneous group of learners. In parallel, adaptive learning and its analytic ecosystem are assessed by impact criteria such as compatibility, flexibility, etc. We conclude that effective adaptive learning systems need to have a broad range of learner evaluation methods, must obviously be feasible to implement, depending on the stakeholders' capabilities, and must be able to adapt to all the potential target learners. Given this, the ecosystem's performance is assessed through its capacity to adapt, mentor, recommend, and intervene. To improve its performance and quality, and to adapt to learners' needs, the constructed educational models will have to be transformed into adaptive learning models. Meanwhile, the main sustainability issue is the integration of technologies, which is nonetheless needed to ensure the reliability and variety of data analysis, as well as to enhance decision-making. This is especially true when adaptive learning development is affected by a great number of external variables.

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